RECENT CHANGES IN THE EUROPEAN EMPLOYMENT STRUCTURE: THE ROLES OF TECHNOLOGY AND GLOBALIZATION

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ABSTRACT

This paper shows that recent changes in the employment structure of 16 European countries have been similar to those taking place in the US and the UK. At least since the early 1990s, the employment shares of high-paid professionals and managers as well as low-paid personal services workers have increased at the expense of the employment shares of middling manufacturing and routine office workers – a process known as job polarization. To explain job polarization, we present a simple model to capture the many channels that determine the demand for different types of labor and several new datasets are exploited to test its predictions in various ways. In line with recent evidence for the US and the UK, our estimates are consistent with the task-biased hypothesis of technological progress proposed by Autor, Levy and Murnane (2003) – that technology can replace human labor in routine tasks but (as yet) cannot replace human labor in non-routine tasks. We find some support for the hypothesis that mainly routine jobs have been offshored recently, although the estimated employment impact is smaller and less pervasive than that of technological progress. Finally, we show that institutional differences between countries and changes in the relative demand for labor due to changes in income or income inequality cannot explain much of the variation in employment.

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1. INTRODUCTION

The structure of employment is constantly changing. Although the net change is generally towards better paying occupations (albeit at a modest pace), this process often causes alarm, mainly because individuals who have invested a lot in a particular skill may find the return to that skill drops as it becomes all but impossible to find a job that uses that skill.[1]

Economists have had a lot to say about the driving forces behind changes in the occupational structure of employment. They emphasize the importance of technological change, globalization (partly driven by technology, but perhaps partly also an independent force from declining man-made barriers to trade), and institutions. In the 1980s and 1990s, the dominant view among labor economists was that technology was more important than trade as a driving-force behind changes in the structure of employment (see, for example, Johnson 1997; Desjonqueres, Machin and Van Reenen 1999; Autor and Katz 1999), and that technological change was biased in favor of skilled workers, leading to the hypothesis of skill-biased technological change or SBTC (see, for example, Krueger 1993; Berman, Bound and Griliches 1994; Berman, Bound and Machin 1998; Machin and Van Reenen 1998; Autor, Katz and Krueger 1998). More recently, views have been shifting somewhat.

Firstly, there is a more nuanced view of the impact of technological change on the demand for different types of labor. Autor, Levy and Murnane (2003) argue persuasively that technology can replace human labor in routine tasks – tasks that can be expressed in step-by-step procedures or rules – but (as yet) cannot replace human labor in non-routine tasks. The ALM (or task-biased technological change) hypothesis is intuitively plausible and they provide evidence that industries in which routine tasks were heavily used have seen the most adoption of computers, and this has reduced the usage of routine tasks in those industries. Although low-skill production-line jobs

[1] For example, the issue of offshoring of US jobs has become a major political issue - see the accounts in Blinder [2006, 2007] and Mankiw and Swagel [2006].

in manufacturing can be characterized as ‘routine’, so can many more skilled craft jobs and many clerical jobs that never were the lowest paid jobs in our economy. In contrast, many of the worst-paying jobs, for example in housekeeping, hotel and catering and personal care, are non-routine in nature and therefore have been relatively unaffected by technological change. As a result, the distribution of jobs is ‘polarizing’ with faster employment growth in the highest and lowest-paying jobs and slower growth in the middling jobs. Recent empirical work has shown how this has been happening in the US (Autor and Dorn 2009; Autor, Katz and Kearney 2006, 2008; Smith 2008), the UK (Goos and Manning 2007), and West-Germany (Spitz-Oener 2006 and Dustmann, Ludsteck and Schönberg 2009).

Secondly, concerns about the impact of globalization on employment in OECD economies have also been changing. The concern in the 1980s and 1990s was largely about the displacement of manufacturing as a whole (i.e. as an industry) to lower-wage countries. More recently, the focus of concern has been about the relocation of certain parts of the production process (generally, specific occupations) to developing countries, a process often called “offshoring”.[2] The rapid growth of countries like India and China in recent years has made many economists feel that globalization is having a more powerful effect on the structure of employment now than in the 1980s. For example, Blinder (2007, 2009) and Blinder and Krueger (2009) estimate that approximately 25% of US jobs might become offshorable within the next 20 years. Especially offshoring of service activities (as opposed to material offshoring) has become a popular topic in recent years (IMF World Economic Outlook 2007; Molnar, Pain and Taglioni 2007). However, Lui and Trefler (2008) examine the employment effects of service offshoring by US companies to un-affiliated firms abroad as well as the employment effects of service inshoring – the sale of services to US firms by

[2] Throughout this paper, by “offshoring” we mean the use of intermediate inputs imported from abroad, also known as “offshore outsourcing”. This is different from “outsourcing” or the use of intermediate inputs imported from abroad or produced domestically. The difference between offshoring and outsourcing is important here since our model and data only capture the offshore component of outsourcing.

unaffiliated firms abroad. They only find small positive effects of service inshoring and even smaller negative effects of service offshoring.

In this paper we seek to identify the employment impact of task-biased technological progress and offshoring in 16 European countries. It is likely that the forces of technology and offshoring are having similar effects on employment within all these countries. However, in many of the European countries there is an additional concern – that wage-setting institutions compress relative wages so that there is a dearth of low-wage jobs in these economies, and that this explains, in some part, the persistently high rates of unemployment in many of these countries (an idea associated with Krugman [1994] – but see Nickel and Bell [1995,1996]). Therefore, this paper also accounts for the role of institutions in examining the employment impact of task-biased technological progress and offshoring.

Finally, besides the impact of task-biased technological progress and offshoring, relative employment could also change due to changes in relative product demand following changes in income or income inequality. For example, Clark (1957) finds that the income elasticity of demand for services is greater than unitary, suggesting that the observed rise in low-paid service employment can partially be explained by an increase in income if preferences are non-homothetic. And even if preferences are homothetic, Manning (2004) and Mazzolari and Ragusa (2007) argue that wage gains for high-income workers increase their opportunity cost of doing domestic chores, leading to an increase in the relative demand for some low-paid service workers. However, a recent study by Autor and Dorn (2009) examines the growth in low-skilled service jobs in the US allowing for many different channels to affect employment. They argue that task-biased technological progress has had an important direct effect on employment without much evidence in support of the hypothesis that the rise in low-skilled service jobs is driven by the relative increase in consumer demand for personal services. Besides estimating the impact of technological progress or offshoring, this paper therefore also examines the employment impact of changes in income and differences in income inequality.

The remainder of this paper is organized as follows. Section 2 gives evidence as to how the employment structure in the European countries is changing. Section 3 then provides a simple theoretical framework to organize our thoughts about the channels through which technology and offshoring affect the demand for different jobs. Section 4 describes the data we use. The fifth section presents our empirical results.

2. A PICTURE OF CHANGES IN THE EUROPEAN JOB STRUCTURE

To provide a snapshot of changes in the European job structure, Table 1 shows the employment shares of occupations and their percentage point changes between 1993 and 2006 after pooling employment for each occupation across 16 European countries.[3] This table shows that the high-paying managerial and professional occupations experienced the fastest increases in their employment shares. On the other hand, the employment shares of office clerks; craft-related occupations; and machine operating and assembling occupations, which pay around the mean occupational wage, have declined. Similar to patterns found for the US and UK, several low-paid service occupations have increased their employment shares: customer service clerks; personal and protective service workers; and sales and service elementary occupations. This is an indication that, at the level of the EU as a whole, there is job polarization occurring in which employment rises fastest for the best-paying jobs and falls most for those in the middle of the earnings distribution.

We illustrate this further by plotting the change in occupation-industry employment shares pooled across the European countries against 1994 UK mean

[3] The 16 countries are listed in Table 2. Since all countries do not have data for the entire time-span of 1993-2006, we calculate average annual changes for each country and use these to impute the employment shares in 1993 and/or 2006 where they are not available. Section 4 provides further details on how employment and wages have been measured.

earnings at the occupation-industry level[4] together with a fitted kernel regression line – shown in Figure 1. We see a U-shaped relationship, indicating relatively faster employment growth in high paying and some low paying jobs. At the European level, job polarization does seem to have occurred over the past 14 years.

However, we have not yet assessed to what extent this process occurs to the same degree in all countries in our sample. Table 2 therefore examines country heterogeneity in employment polarization by dividing the occupations listed in Table 1 into three groups: the four lowest paid occupations (mainly non-routine jobs in services), nine middling occupations (mainly routine manufacturing jobs) and the eight highest paying occupations (mainly non-routine jobs in services). We then compute the percentage point change in employment share for each of these groups in each country. Table 2 confirms that employment polarization is pervasive across European countries – the share of high-paying occupations increases relative to the middling occupations in all countries but Portugal, and the share of low-paying occupations increases relative to the middling occupations in all countries.[5] However, Table 2 also shows there is some country heterogeneity in the extent of polarization. We aim to explain this heterogeneity in our empirical analysis by accounting for differences in labor market institutions between these countries.

3. A SIMPLE MODEL

We sketch a simple conceptual framework for thinking about two potential causes of the changes in the job structure observed in the previous section: task-biased technological progress and offshoring. Task-biased technological progress assumes that technological progress complements with or substitutes for certain tasks used in

[4] We use the UK occupation-industry wage (from the LFS) since there is no European-wide equivalent available. Results should not be affected given the high correlation between wage ranks. We use wages from the initial year because of their potential endogeneity: rather than using 1993, we use 1994 because it has a significantly larger sample size.

[5] This result is upheld when we add customer service clerks, a middle-paid service occupation, to the four lowest-paid occupations: indeed, in this case, we observe an increase in the share of high- and low-paying occupations relative to the middling occupations in all countries.

production. Moreover, the recent concern about offshoring has been about the relocation of certain parts of the production process rather than the displacement of an industry as a whole. We therefore assume that tasks and the offshorability of parts of the production process are best captured by workers' occupations – describing what it is that workers do on the job.

In particular, in the model presented below we assume that the production of goods or services requires the use of several tasks and that each task is produced using labor of a certain occupation together with some other input. Moreover, we will assume that occupations are relative p-complements or p-substitutes to capital (to capture technological progress) or foreign labor (to capture offshoring). Important for the empirical analysis presented later in this paper, we will also assume that the technology to produce one unit of a certain task is common across industries – a strong assumption, albeit one that has been used in other models (e.g. Grossman and Rossi-Hansberg 2007)[6] and that we do seek to test later.

3.A The production of goods and the demand for tasks

Assume that output is produced by combining certain building blocks that we will call tasks. Some industries are more intensive users of some tasks than others (and some industries may not use some tasks at all). In particular, assume the following CES production function for good *i* using tasks $T_1, T_2, ..., T_J$ as inputs:

(1) $$Y_i(T_{i1}, T_{i2}, ..., T_{iJ}) = \left[\sum_{j=1}^{J} \left(\beta_{ij} T_{ij} \right)^{\eta} \right]^{\frac{1}{\eta}} \text{ with } 0 < \eta < 1 .$$

The corresponding demand for task *j* conditional on Y_i is:

(2) $$T_{ij}\left(c_1, c_2, ..., c_J \mid Y_i\right) = Y_i \frac{1}{\beta_{ij}} \left(\frac{c_j}{\beta_{ij}} \right)^{-\frac{1}{1-\eta}} \left[\sum_{j=1}^{J} \left(\frac{c_j}{\beta_{ij}} \right)^{-\frac{\eta}{1-\eta}} \right]^{-\frac{1}{\eta}}$$

[6] Though they assume that domestic and foreign labor are perfect substitutes.

$$= Y_i \frac{1}{\beta_{ij}} \left(\frac{c_j}{\beta_{ij}} \right)^{-\frac{1}{1-\eta}} \Gamma_i^{\frac{1}{1-\eta}}$$

with c_j the real unit cost of using task *j* and Γ_i real industry marginal costs.[7]

3.B The demand for labor conditional on output

To determine the supply of tasks, we assume that task-level output can be produced using labor of a certain occupation and some other input. In particular, assume that in industry *i* tasks are produced using labor of type *j*, N_{ij}, and any other input, K_{ij}, according to:

(3) $$T_{ij}(N_{ij}, K_{ij}) = \left[N_{ij}^{\rho_j} + K_{ij}^{\rho_j} \right]^{\frac{1}{\rho_j}} \text{ with } 0 < \rho_j < 1$$

where the technology to produce task *j* is common across industries. In this specification the input apart from labor, K_{ij}, should be interpreted very loosely to mean other inputs that is not employment.

The associated demand for labor of type *j* conditional on task output is given by:

(4) $$N_{ij}(w_j, r \mid T_{ij}) = T_{ij} w_j^{-\frac{1}{1-\rho_j}} \left[w_j^{-\frac{\rho_j}{1-\rho_j}} + r^{-\frac{\rho_j}{1-\rho_j}} \right]^{-\frac{1}{\rho_j}}$$

where w_j is the real wage in occupation *j* and r the real price of the other input. Substituting (2) into (4) and taking logs, we can now derive an expression for the demand for labor conditional on industry output:

(5) $$\log N_{ij}(w_j, r \mid Y_i) = \log Y_i + \frac{\log \Gamma_i}{1-\eta} + \frac{\eta}{1-\eta} \log \beta_{ij} - \left[\frac{1-s_j}{1-\rho_j} + \frac{s_j}{1-\eta} \right] \log w_j + \left[\frac{1}{1-\rho_j} - \frac{1}{1-\eta} \right] (1-s_j) \log r$$

where s_j is the cost share of labor in the production of task *j*.

[7] By "real" we mean relative to the aggregate output price index.

3.C The unconditional demand for labor

One might want to go further and not condition on industry output. To do this, we need an industry demand curve. So let us assume an aggregate CES consumption function such that the demand for good *i* is given by:

$$\text{(6)} \qquad \log Y_i = \log L + \log(Y/L) - \frac{1}{1-\gamma}\log P_i$$

with L the size of the population and Y real aggregate income, P_i the price of good *i* relative to the aggregate price index and $1/(1-\gamma)$ the elasticity of substitution between goods in consumption with $0<\gamma<1$. Note that the logarithm of total demand for output of industry *i* is unitary proportional to the logarithm of the size of the population as well as the logarithm of average real income per capita. The proportionality between the demand for good *i* and real average income per capita follows directly from the assumption that preferences are homothetic.

Further assume that firms in each industry maximize profits by setting prices as a constant mark-up over marginal costs, or $\log P_i = \log\Gamma_i - \log\gamma$. This gives the following equation for the demand for good *i*:

$$\text{(7)} \qquad \log Y_i = \frac{\log\gamma}{1-\gamma} + \log L + \log(Y/L) - \frac{1}{1-\gamma}\log\Gamma_i$$

Substituting (7) into (5), we then get the following expression for unconditional labor demand:

$$\text{(8)} \qquad \begin{aligned} \log N_{ij}(w_j,r) &= \frac{\log\gamma}{1-\gamma} + \log L + \log(Y/L) + \left[\frac{1}{1-\eta} - \frac{1}{1-\gamma}\right]\log\Gamma_i \\ &+ \frac{\eta}{1-\eta}\log\beta_{ij} - \left[\frac{1-s_j}{1-\rho_j} + \frac{s_j}{1-\eta}\right]\log w_j + \left[\frac{1}{1-\rho_j} + \frac{1}{1-\eta}\right]\left(1-s_j\right)\log r \end{aligned}$$

This framework captures many different channels of influence on labor demand. Of course, many very specific assumptions about functional forms have been made and the model does treat all wages of different occupations as given – an extension would be to model supply to different occupations.[8] However, the simple framework presented above does have the virtue of leading to empirical equations that are relatively straightforward to estimate. In particular, this model predicts that employment in occupation *j* in industry *i* will be affected (all else equal):

a) Positively by the size of the population (*L*) and real average income per capita (*Y/L*), reflecting that higher real aggregate income increases the demand for labor of type *j* in industry *i*. Moreover, if the production function exhibits constant returns to scale, the logarithm of the demand for labor of type *j* is unitary proportional to the logarithm of population size and the logarithm of average income per capita if preferences are homothetic.

b) Ambiguously by real industry marginal costs (Γ_i). The first term in square brackets reflects that, for example, industry marginal costs will increase if the marginal cost of producing any task that is not task *j* increases. This increase in industry marginal costs will increase the demand for labor of type *j*, reflecting the shift towards type *j* labor to produce one unit of good *i*. The second term in square brackets captures that higher industry marginal costs will increase the price of good *i*, which decreases output and therefore labor demand.

c) Positively by the relative productivity of task *j* in the production of good *i* (β_{ij}). The intuition is that an increase in β_{ij} shifts the production of each unit of good *i*

[8] Autor and Dorn (2009) present a general equilibrium framework to analyze the impact of task-biased technological progress on occupational employment and wages. They assume a somewhat different production structure from the one presented above and the paper doesn't explicitly derive an expression for labor demand to compare to equation (8). Nevertheless, both models produce qualitatively similar predictions about changes in labor demand. Firstly, they also find that a decrease in the price of capital in the long-run leads to a decrease in the demand for labor if the elasticity of substitution between goods in consumption is sufficiently small compared the elasticity of substitution between inputs in production (as captured by the third term in equation (8) in square brackets). Secondly, their model also predicts that a decrease in the price of capital in the long-run leads to a decrease in the demand for labor that is decreasing in the cost share of labor (as captured by the last term in equation (8) in brackets). Thirdly, as we will assume in section 3.D below, Autor and Dorn (2009) assume that routine labor and capital are relative p-substitutes in production relative to non-routine labor and capital, thereby predicting an increase in employment shares in high-paid and low-paid non-routine jobs at the expense of employment in middling routine occupations. Finally, because Autor and Dorn (2009) assume aggregate labor supply is fixed even in the long-run, changes in relative wages must ultimately be positively correlated with changes in relative labor demand due to technological progress. In this paper, we do not account for the possibility that technological progress or offshoring also affects relative wages. Although this is a clear theoretical shortcoming, Section 4.B below argues that the occupational wage ranking used in the analysis below is very stable within each country over time and across countries at each point in time.

towards a more intensive use of task *j* which increases the demand for type *j* labor in that industry.

d) Negatively by the real cost of labor of type *j* (w_j).The first term in square brackets reflects that an increase in $\log w_j$ results in a shift away from using labor in the production of each unit of task *j*. The second term in square brackets reflects the negative employment impact due to a shift away from using task *j* in the production of each unit of good *i*.

e) Ambiguously by the real cost of the other input (r). The intuition for this is that an increase in $\log r$ will result in a shift toward labor in producing one unit of task *j*. However, there will be a shift away from using task *j* to produce one unit of good *i*, which decreases the demand for labor.

3.D Biased technological progress and offshoring

Assume that technological progress or an increase in offshorability can be summarized as a secular decrease in the real price of capital or foreign labor or a secular decrease of $\log r$ in the model discussed above. To capture the routinization hypothesis, further assume that the elasticity of substitution between routine labor and capital is larger than the elasticity of substitution between non-routine labor and capital (that is, $1/(1-\rho_j)$ is larger for routine occupations than for non-routine occupations). Said differently, routine occupations and capital are relative p-substitutes.[9] Similarly, occupations that are more offshorable are assumed to be relative p-substitutes with foreign labor.

This model would then predict a secular decrease common across industries in the relative demand for routine labor, capturing task-biased technological change,

[9] Note that if $\rho_j > \eta$ for routine occupations and $\rho_j < \eta$ for non-routine occupations, then routine occupations and capital are p-substitutes and non-routine occupations and capital are p-complements conditional on industry output. However, the regression analysis below only captures the *relative* p-substitutability between routine occupations (relative to non-routine occupations) and capital and the *relative* p-substitutability between more offshorable occupations (relative to less offshorable occupations) and foreign labor.

and a relative decrease common across industries in the relative demand for offshorable occupations, capturing the increased use of offshoring over time. Note that the variation in employment predicted by both technological progress and offshoring is different from the variation predicted by, for example, changes in population size or average income per capita. If changes in population size or average income per capita would be the only drivers determining employment, one would expect to see variation in employment that is industry rather than occupation specific. This is the way in which our model assumes how different fundamental drivers affect employment – assumptions that we do seek to test in various ways in the remainder of this paper.

4. DATA

In this section we describe our main sources of data on employment and wages, our measures of technological change, offshoring, and institutions, as well as data on output, industry marginal costs and income.

4.A Employment

Our main source for employment data over time by industry and occupation is the harmonized individual-level European Union Labor Force Survey (ELFS) for the period 1993-2006. The ELFS contains data on employment status, weekly hours worked, 2-digit International Standard Occupational Classification (ISCO) codes and 1-digit industry codes from the Classification of Economic Activities in the European Community (NACE revision 1). Throughout this paper, we use weekly hours worked as a measure for employment, although our results are not affected by using persons employed instead.

Out of the 28 countries available in the ELFS, we exclude 9 new EU member countries[10], 2 candidate member countries[11] and Iceland because of limited data availability. We also discarded Germany from the ELFS because of its too small sample size and limited time span. Data for the remaining 15 European countries (Austria, Belgium, Denmark, Finland, France, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden and the United Kingdom) is used in the analysis.

We supplement our ELFS sample with the German Federal Employment Agency's IABS dataset, which is a 2% random sample of German social security records for the period 1993-2002. For each individual it contains data on occupation and industry, as well as several demographic characteristics (among others, region of work, full-time or part-time work). We drop workers who are not legally obliged to make social security contributions (some 9% of all observations) because for them the IABS is not a random sample. Lacking a measure of hours worked, we use time-varying information on average weekly hours worked for full-time and part-time workers in both East- and West-Germany, obtained from the European Foundation for the Improvement of Living and Working Conditions (Eurofound) to proxy for total hours worked in IABS occupation-industry-year cells.[12] We then manually convert the German occupation and industry codings to match ISCO and NACE in the ELFS.[13]

Having combined the ELFS with the IABS, we drop some occupations and industries from the ELFS sample – those related to agriculture and fishing because they do not consistently appear in the data and because OECD STAN industry output data is not suited for comparison across countries for these sectors (see Section 4F); and those related to public administration and education because German civil servants are not liable to social security and therefore not included in the IABS, and

[10] Cyprus, the Czech Republic, Estonia, Hungary, Lithuania, Latvia, Poland, Slovenia and Slovakia
[11] Romania and Bulgaria
[12] Our results are robust to restricting the German sample to full-time workers.
[13] Since we could not find an exact match for all codes, we have two fewer ISCO occupations and three fewer NACE industries for Germany.

because OECD STAN net operating surplus data is not reliable for these two sectors. Our results are never affected by the exclusion of these occupations and industries.

4.B Wages

Since the ELFS does not contain any earnings information, we obtain time-varying country-specific occupational wages from the European Community Household Panel (ECHP) and European Union Statistics on Income and Living Conditions (EU-SILC). These datasets contain wages for individuals in all 16 countries except Finland and Sweden. The ECHP contains gross monthly wages for the period 1994-2001, whereas the EU-SILC reports gross monthly wages for the period 2004-2006. For the UK, we use the gross weekly wage from the Labor Force Survey (LFS) because it contains many more observations and is available for 1993-2006. All wages have been converted into 2000 Euros using harmonized price indices and real exchange rates.

To match our employment dataset, we construct an occupational wage measure weighted by hours worked. Given that the occupational wage ranking is very stable within countries over time (see the next paragraph), we impute wages for missing years by setting them equal to the average wage across the closest years where original data is available. For Finland and Sweden, we use aggregate OECD data to construct occupational wages using the following formula:

$$w_{jct} = \overline{w}_{ct} + \frac{\sigma_{ct}}{\sigma_{DE,t}}\left(w_{j.DE,t} - \overline{w}_{DE,t}\right)$$

where w_{jct} is the average wage in occupation *j*, in country *c* (in this case, Finland or Sweden) at time *t*, $\overline{w}_{ct}$ is the median wage in country *c* at time *t*, and σ_{ct} is a measure of wage inequality in country *c* at time *t* (specifically the ratio of the 90^{th} to the 10^{th} percentile derived from the OECD). The variables with the subscript *DE* refer to the value of those variables in Germany. Two implicit assumptions underlie the validity of this construction: that occupational wage structures are very highly correlated across countries; and that the level of occupational wage differentials is related to wage inequality in the country.[14] Finally, in each country wages have been smoothed by pooling together all years for each occupation and estimating a model in which the dummy on occupation varies smoothly with a quadratic time trend.

Although sample sizes in the ECHP and EU-SILC are relatively small, it is assuring that the wage rank of occupations is intuitive, and highly and significantly correlated within countries over time. Table 3 provides the wage rank of occupations in 1993 and 2006, averaged across the 16 countries and rescaled to mean zero and unit standard deviation. The ranking is as expected, with corporate managers and professionals being the most highly paid, elementary and personal services workers the lowest paid, and manufacturing and office workers somewhere in between. This ranking is very stable within countries over time, with Spearman rank correlation coefficients of around 0.90, and all significant at the 1% level.

4.C Task-biased technological progress

For task measures we use data from the December 2006 version of the Occupational Information Network (ONET) database. ONET is a primary source of occupational information, providing comprehensive information on key attributes and characteristics of workers in US occupations. It is a replacement for the Dictionary of Occupational Titles (DOT) which has been used in earlier research, notably by Autor, Levy and Murnane (2003). ONET data comes from job incumbents, occupational analysts and occupational experts and is collected for 812 occupations which are based on the 2000 Standard Occupational Code (SOC). We manually converted the 2000 Standard Occupational Code (SOC) used in the ONET data to ISCO.[15]

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[14] We do indeed find that the wage ranking of occupations across countries at any point in time is very stable: in 2001, for instance, the mean Spearman rank correlation coefficient is 0.87, with a standard deviation of 0.05.

[15] There is no time variation in ONET, which would be problematic for the analysis below if the task composition within occupations is changing over time. However, using similar DOT measures across US occupations and over time, Goos and Manning (2007) find that most of the overall changes in mean task measures happened between and not within occupations. Also note that ONET does not contain any variation in job task measures that would exist between individuals with the same occupation. However, Autor and Handel (2009) use the individual level PDII (Princeton Data Improvement Initiative) data to show that occupation is the dominant predictor for the variation in the task measures that are also used in this paper.

One part of ONET consists of some 100 variables related to worker characteristics, worker requirements and general work activities. We select 96 of these task measures which are closest to the DOT task requirements used by Autor, Levy and Murnane (2003) and Autor and Dorn (2008). Each respondent is asked how important the task is for her job, where importance ranges from 1 (not important at all) to 5 (extremely important). Each of the 96 ONET variables is categorized into one of three groups: *Abstract*, *Routine* or *Service*.

We choose these three measures following Autor and Dorn (2009) to capture technological progress biased towards occupations intense in non-routine tasks – the ALM hypothesis. Routine tasks are those which computers can perform with relative ease, such as jobs that require the input of repetitive physical strength or motion, as well as jobs requiring repetitive and non-complex cognitive skills. The non-routine dimension is split up into Abstract and Service to capture the different skill content of these non-routine tasks: examples of Abstract and Service tasks are "complex problem solving" (e.g. needed by engineers and medical doctors) and "caring for others" (e.g. needed by hairdressers and medical doctors), respectively. That is, although Abstract tasks are non-routine tasks mainly carried out by highly educated workers, Service tasks are non-routine tasks that workers with different levels of education may perform.

Examples of ONET variables used as measures of Abstract tasks are "critical thinking", "judgment and decision making", "complex problem solving", "interacting with computers" and "thinking creatively". Examples of Routine task measures are "arm-hand steadiness", "manual dexterity", "finger dexterity", "operation monitoring", and "estimating the quantifiable characteristics of products, events, or information". Examples of Service task measures are "social perceptiveness", "service orientation", "assisting and caring for others", "establishing and maintaining interpersonal relationships", "selling", and "performing for or working directly with the public".

For each of these three task measures, we construct a principal component across SOC occupations, which we collapse to the ISCO level weighted by US employment in each SOC cell taken from ONET. Columns (1) through (3) of Table 4 show the values of these three principal components, with mean zero and unit standard deviation, for 2-digit ISCO occupations ranked by their mean 1993 wage across the 16 European countries. Figure 2 makes this information more accessible by showing how the Abstract, Routine and Service task measures are distributed over the occupations ranked by their mean wage. Three different types of jobs can be identified. Firstly, high paid jobs (located mainly in the service sector) are intense in Abstract tasks, and also use Service tasks intensively. Secondly, jobs paying around the overall average wage or somewhat less (predominantly found in manufacturing) are intense in Routine tasks. Finally, low-paid jobs in services are relatively intense in Service tasks, and less intense in Routine tasks than the middle-paid jobs.

To capture the idea of skill-biased technical change or SBTC, the fifth column of Table 4 also presents the mean educational attainment by occupation. This variable derives from a three-level education variable (categorized with the International Standard Classification of Education, or ISCED) available in the ELFS, which we average by occupation across countries[16]. One can see the high correlation between the wage rank and educational attainment across occupations.

4.D Offshoring

There are a number of approaches to measuring the impact of offshoring in the literature. Typically, use is made of measures of foreign direct investment by OECD countries or measures of imports in total GDP; the share of intermediate goods imports in total imports; or the share of imports from non-OECD countries in total imports. This type of data is available at the country-industry-time level but never at the occupation level. However, according to our model we need an occupation-specific

[16] Occupational education levels are very highly correlated among countries, the average correlation coefficient being 0.93 with a standard deviation of 0.03.

measure of offshoring to separate out its impact from the impact of technological change. Blinder (2007, 2009) uses ONET to provide a measure of which US occupations are potentially offshorable *in the future*, based on whether the work done in that occupation can be delivered over a distance (physically or electronically) without quality degradation. Blinder and Krueger (2009) use the individual level PDII (Princeton Data Improvement Initiative) data to construct alternative measures of offshorability. The authors conclude that their preferred measure of offshorability is derived by professional coders based on a worker's occupational classification. Although we are not professional coders and our occupational measure of offshorability is derived from firm level rather than individual level data, it is reassuring to see that the distribution of our measure of offshorability across occupations, education and income levels that we discuss below corresponds largely to the preferred measure by Blinder and Krueger (2009).

We obtain a measure of offshorability from the European Restructuring Monitor (ERM) of the European Monitoring Centre on Change (EMCC), which is a part of Eurofound. ERM is available online[17] and provides summaries of news reports (so-called fact sheets) since 2002 about companies located in Europe that announce offshoring plans. These fact sheets contain information on the company that is offshoring part(s) of its production process, such as the country and the industry in which it operates, how many workers are employed nationwide or in that particular location, how many jobs are being offshored and to which country, and, most importantly for our purposes, what kinds of jobs (i.e. which occupations) are being offshored.

We processed 415 fact sheets (covering May 31st, 2002 up to June 30th, 2008), or cases of offshoring, to construct an index of how offshorable the different occupations are. We summed the number of cases for each ISCO occupation[18], and generated a rank by rescaling the number of cases across occupations to a

[17] http://www.eurofound.europa.eu/emcc/index.htm
[18] Note that one fact sheet usually contains more than one ISCO occupation that is being offshored.

distribution with mean zero and unit standard deviation. The fourth column of Table 4 shows this occupation-level measure of offshorability. It can be seen from Table 4 that although routine occupations (e.g. machine operators, office clerks) are the ones that are offshored most often, some non-routine occupations (engineering associate and other associate professionals; customer service clerks; models, salespersons and demonstrators which includes call-centre workers) are still much more offshorable than others (managers, professionals, elementary sales and service workers). Figure 2 shows that, as a result, offshorability has a distribution across occupations that is somewhat different from that of Routine task importance. This indicates that offshoring predicts an impact on the relative employment growth in some occupations that is different from the predicted impact of task-biased technological progress.

4.E Institutions

For measures of the importance of labor market institutions in the 16 European countries we use information on overall, upper-tail and lower-tail wage inequality to generally capture institutional variation across countries – see Lemieux (2008) for a discussion of how institutions are related to wage inequality. Ideally, one would like to have measures of wage inequality preceding our employment time span to avoid problems of simultaneity in the estimates below. Rather than using the ECHP, EU-SILC and LFS discussed in section 4.B, we obtained information about wage dispersion between 1990 and 1994 for 12 of our 16 countries from the OECD.[19] Averaging over those four years, we use the ratio of the 90th wage percentile to the 10th wage percentile in each country as a measure of overall wage inequality, as well as the 90th wage percentile to the 50th wage percentile and the 50th wage percentile to the 10th wage percentile as measures of upper- and lower-tail inequality, respectively.

4.F Industry output and industry marginal costs

[19] The four missing countries are Austria, Greece, Luxembourg and Norway. Constructing measures of overall wage inequality using the wage data discussed in section 4.B for all 16 countries does not qualitatively change our results.

Measures of industry output and industry marginal costs are taken from the OECD STAN Database for Industrial Analysis. Each of our 16 countries except Ireland is included in STAN. This data covers the period 1993-2006 for all 15 of these countries. STAN uses an industry list for all countries based on the International Standard Industrial Classification of all Economic Activities, Revision 3 (ISIC Rev.3) which covers all activities (including services) and is compatible with NACE revision 1 used in the ELFS.[20]

The measure of output used in the analysis below is value added, available in STAN as the difference between production (defined as the value of goods and/or services produced in a year, whether sold or stocked) and intermediate inputs. Value added comprises labor costs, capital costs and net operating surplus. To obtain variation in output, value added has been deflated using industry-country-year specific price indices available from STAN for all countries except Ireland, Sweden and the UK.

Finally, we approximate real industry marginal costs as the difference between net operating surplus and production, divided by production. This gives an estimate of the real average cost per Euro of output. We use this measure to proxy for the variation in real industry average costs – which in our model is identical to real industry marginal cost – since both are positively correlated with factor prices.

5. ESTIMATION RESULTS

The starting-points for our empirical investigation are equations (5), (7) and (8). Introducing country and time subscripts (denoted by *c* and *t* respectively), we have

[20] Due to limited data on net operating surplus for the NACE industry "Private households with employed persons", we have one less industry when using STAN data in our regressions. The exceptions are France, Portugal, Spain and the UK, where this industry is instead included in "Other community, social and personal service activities" in STAN. Although the industry "Private households with employed persons" mainly employs low-paid service workers and its employment share has increased from 0.82% in 1993 to 0.90% in 2006, it is too small to be an important factor of job polarization.

that the conditional demand for labor, the demand for good or service *i* and the unconditional demand for labor are respectively given by equations (9), (10) and (11):

(9)
$$\log N_{ijct} = \log Y_{ict} + \frac{\log \Gamma_{ict}}{1-\eta} + \frac{\eta}{1-\eta}\log \beta_{ij}$$
$$-\left[\frac{1-s_j}{1-\rho_j} + \frac{s_j}{1-\eta}\right]\log w_{jct} + \left[\frac{1}{1-\rho_j} - \frac{1}{1-\eta}\right]\left(1-s_j\right)\log r_t$$

(10)
$$\log Y_{ict} = \frac{\log \gamma}{1-\gamma} + \log L_{ct} + \log(Y_{ct} / L_{ct}) - \frac{1}{1-\gamma}\Gamma_{ict}$$

(11)
$$\log N_{ijct} = \frac{\log \gamma}{1-\gamma} + \log L_{ct} + \log(Y_{ct} / L_{ct}) + \left[\frac{1}{1-\eta} - \frac{1}{1-\gamma}\right]\log \Gamma_{ict} + \frac{\eta}{1-\eta}\log \beta_{ij}$$
$$-\left[\frac{1-s_j}{1-\rho_j} + \frac{s_j}{1-\eta}\right]\log w_{jct} + \left[\frac{1}{1-\rho_j} - \frac{1}{1-\eta}\right]\left(1-s_j\right)\log r_t$$

5.A Testing the model's assumptions

In this section we try to provide some further evidence on the adequacy of our model. One way to test our model is to decompose occupational employment share changes into within- and between-industry components. If our model is correct, we would expect within-industry changes in employment shares to be negative for routine or offshorable occupations and positive for non-routine or non-offshorable occupations (assuming routine or offshorable occupations and capital or foreign labor are relative p-substitutes). The between-industry changes in employment shares of routine (non-routine) occupations are also expected to be negative (positive), if routine (non-routine) occupations are relative gross substitutes (gross complements) with technology or offshoring. Table 5 shows that these expected patterns largely hold up in the data: the employment shares of managerial and professional occupations increase both within and between industries; the employment shares of routine occupations in manufacturing generally decrease within and between industries; and the employment shares of several low-paid service occupations increase within and between industries.

As a more comprehensive test of our model, we perform an analysis of variance (ANOVA) of the dependent variable in (11). The objective of this ANOVA is to assess whether the channels which our model highlights, namely country-year (capturing variation in aggregate income), industry-country-year (capturing variation in industry marginal costs), industry-occupation (capturing variation in the way in which tasks are combined to produce one unit of output) and occupation-year (capturing variation in wages, technological progress or offshoring) effects are present in the dependent variable. We can identify these channels by controlling for all other possible variation that could make the F-test statistic on each of these channels significant. For instance, in order to identify technological progress or offshoring through occupation-year effects, one should control for occupation and year effects separately.[21] Table 6 performs this analysis of variance. It can be seen from column (1) that country-year, industry-country-year, industry-occupation, and occupation-year interactions are all significant.

Our model assumed that technological progress and offshoring affect the task production technology similarly in all industries but do not affect the way in which tasks are combined to produce one unit of output. Controlling for all other confounding dimensions, this assumption would be consistent with the presence of industry-occupation variation but the absence of industry-occupation-time variation in employment. Column (2) therefore adds an industry-occupation-time term to the variance decomposition. In line with our model, the industry-occupation-time interaction is not statistically significant.

[21] Note however that some of these controls can be captured by other dimensions of interest. For example, year effects are controlled for by the country-year dimension when isolating occupation-year specific variation in employment that is possibly driven by biased technological progress or offshoring of certain occupations over time.

Finally, column (3) adds an occupation-country-year dimension. If the impact of technology or offshoring varies across countries due to institutional differences, one would expect to see significant variation in employment along this dimension too. However, the table shows that the occupation-year variation in employment seems to be largely common across countries suggesting the employment impact of technological progress or offshoring is pervasive.

5.B. The employment impact of technological progress and offshoring

Having established that there is scope for our model in the data, we estimate labor demand given by equation (9). To capture the effects of technological change, we include the three occupation specific task measures – Abstract, Routine and Service – interacted with a linear time trend. To capture the effects of offshoring we include our offshorability measure for each occupation interacted with a linear time trend. In each regression, we include industry-country-year dummies to capture variation in industry output and industry marginal costs, the country-occupation-year specific log wage and dummies for occupation-industry cells to control for industry specific task technologies.[22] To account for serial correlation across years, we cluster standard errors by country-occupation-industry. We start with estimates that assume the pace of change for both technology and offshoring to be the same in all countries. Note that because we standardize each task measure and our measure of offshorability to have mean zero and unit standard deviation across occupations, point estimates are comparable between them.

The first results are presented in Table 7A. It can be seen from columns (1) through (3) that employment increases by 1.71% and 1.58% annually for occupations one standard deviation more intense in Abstract and Service tasks, respectively, whereas employment in occupations intense in Routine tasks decreases by an annual

[22] Note that occupational wages could be endogenous to technological progress or offshoring. However, excluding wages from the regressions does not affect our point estimates on these measures.

1.57%. Column (4) shows that employment in occupations that are easily offshored decreases by an annual 0.97%.

The next three columns show that the size of these employment changes for the task measures is only slightly smaller when offshoring is controlled for, and the result that employment increases for Abstract- and Service-intense occupations while employment decreases for Routine-intense occupations holds in all specifications. The employment impact of offshoring is by far the most affected: it is reduced to half its size or less when one of the task measures is controlled for.

Finally, when we include all tasks measures and offshoring in the same regression, as in column (9), employment in Abstract-intense occupations grows 14.6% faster over 1993-2006 (or 1.12% annually), employment in Service-intense occupations grows 3.38% faster (or 0.26% annually- although this point estimate is insignificant), whereas employment in Routine-intense and offshorable occupations grows 9.75% and 4.68% slower (or 0.75% and 0.36% per year), respectively.

We have until now ignored the other hypothesis for the impact of technological change on employment: skill-biased technological change. Within the context of our model, SBTC would imply that tasks vary by the amount of schooling required to perform them, and that technology is a better substitute for tasks the lower their educational requirement. Productivity would then be predicted to increase over time for tasks that can only be performed by highly educated workers. Table 7B therefore addresses the SBTC hypothesis by including the occupational education level interacted with a linear time trend as a regressor.

Column (1) of Table 7B shows that the education level is indeed a significant predictor for employment: on average, occupations that have an education level one standard deviation above the mean education level experience 1.68% higher employment growth per annum. However, if SBTC were to be the correct model, the task-dimension of employment should disappear once the education level is controlled for, bringing the point estimates on Abstract, Routine, and Service task measures (close) to zero. Columns (2) through (4) show that this is clearly not the case. Although higher-educated occupations on average increase their employment faster than lower-educated occupations, the task dimension of employment continues to be a significant predictor of employment changes. These conclusions are upheld in columns (5) through (8), where we control for offshoring. The one but last column enters all task measures together with the education level in one regression, and the last column in addition controls for offshoring. As before, the task-dimension of occupational employment remains important.

However, as has become evident from the literature about job polarization, the most important difference between the hypotheses of skill- versus task-biased technological change is their prediction about employment growth at the lower end of the wage distribution. SBTC predicts that the lowest-paying jobs, which are done by the lowest-educated workers (and which computers can do with relative ease), will disappear faster than middling jobs done by workers with average qualifications (and which computers have more trouble substituting for). On the other hand, the routinization hypothesis predicts that employment in the lowest-paying jobs, which are intense in Service tasks (which computers cannot easily do), increases compared to employment in middling jobs, which are intense in Routine tasks (which computers can do with relative ease).

Table 7C therefore compares the performance of skill-biased technological change with task-biased technological change for employment changes in the 13 lowest-paying occupations.[23] Here the difference in empirical fit between the two views on technological change becomes clear: columns (1)-(5) show that the education level is no longer a significant predictor for changes in occupational employment over time once the Routine or Service task intensity of occupations is controlled for, and the point estimate even becomes negative. The Service intensity of occupations, on the other hand, significantly predicts positive employment effects, and occupations'

[23] The lowest-paying occupations according to the mean European wage: these are the same occupations for which we performed the analyses in the first two columns of Table 2, i.e. excluding the high-paid professional occupations.

Routine intensity significantly predicts negative employment effects. Controlling for offshoring, as is done in columns (6)-(8), does not change these results. It does seem noteworthy, however, that the employment effect of offshoring itself is not as pervasive as the effect of task-biased technological progress. At the lower and middle parts of the occupational wage distribution, offshoring no longer has a significant effect on employment once task-intensities are controlled for, and in some specifications its point estimate becomes very close to zero. All of these results are maintained when we include all task measures, education, and offshoring in one regression as in the final two columns. We reject the hypothesis of skill-biased technological change in favor of the ALM hypothesis.

5.C. Country differences in the employment impact of technological progress and offshoring

Until now, we have assumed that task-biased technological progress and offshoring have the same impact in all 16 countries. Since all countries in our sample can be assumed to be equally affected by similar changes in factor prices, an additional test would be to see whether point estimates do not differ significantly between countries. For example, one could use the specification of the final column of Table 7A and further interact the Abstract, Routine and Service specific time trends with country dummies. Doing this, the F-test statistic for country heterogeneity is only significant for growth in Abstract intense occupations. We also find the employment impact of offshoring to be pervasive – it is associated with slower growth in all countries but Portugal and the UK – although its F-test statistic suggests it is generally less pervasive compared to technological progress.

To investigate this further, Table 8 uses the specification in columns (5)-(7) of Table 7A and adds an interaction of the time trend for each task measure – Abstract, Routine and Service – with measures of wage inequality to capture country-specific differences in labor market institutions. However, none of the interactions are statistically significant, indicating that countries with more overall, upper- or lower-tail wage inequality have not experienced a significantly different task-biased pace of change for employment from countries with lower levels of wage inequality. In a similar vein, one could show that wage dispersion does not significantly explain country variation in the employment impact of offshoring.[24]

5.D. Testing alternative hypotheses for job polarization

So far, technological progress and offshoring have been found to be important in explaining pervasive job polarization in Europe. However, the analysis has not yet been informative about the employment impact of changes in relative product demand following changes in income.

There are two ways in which changes in income can be expected to affect relative employment. Firstly, the relative demand for services increases if preferences are non-homothetic and the income elasticity of demand for services is greater than the demand for goods. Secondly, relative wage gains for high income workers increase their opportunity cost of doing domestic chores and could increase the demand for low-paid personal service workers even if preferences are homothetic. To account for both possibilities in our data, one can test whether the point estimate on log income per capita in equation (10) is unitary and whether it differs by industry. Moreover, one could add to this regression specification a measure of income inequality and its interaction with industry dummies to further capture the possibility that low-paid services are luxury goods or partially involve the marketization of household production.

Results from estimating equation (10) are in Table 9. As predicted by our model, column (1) of Table 9 shows a negative and significant point estimate on industry

[24] The finding that the employment impacts of technological progress and offshoring do not largely depend on institutional differences between countries is also in line with the observation in Goos, Manning and Salomons (2009) that there is no strong cross-sectional link between wage inequality and the occupational structure of employment across our sample of European countries.

marginal cost, a point estimate on log income per capita of 0.92 with a standard error of 0.10 and a point estimate on log population of 1.00 with a standard error of 0.02.

To more explicitly account for the possibility that preferences are non-homothetic, column (2) of Table 9 interacts log income per capita with a vector of industry dummies. Service industries are ranked from high-paid to low-paid by their mean UK wage in 1994 and their point estimates are deviations from the income elasticity for manufacturing. The estimated income elasticity of demand is significantly bigger only for real estate, renting and business activities and significantly smaller for construction as well as hotels and restaurants. In sum, the second column of Table 9 is not very supportive of the idea that the relative growth in both high-paid and low-paid service jobs is best explained by an increase in real earnings.

Finally, column (3) of Table 9 repeats the analysis in column (2) while adding to the regression specification a measure of income inequality and its interaction with industry dummies to further capture the possibility that the demand for low-paid services partially involves the marketization of household production. Just as in column (2), the left panel of column (3) reports the income elasticity by industry. Although the higher income elasticity for financial intermediation and real estate, renting and business activity is intuitive, again the point estimates are not generally supportive of the idea that real income growth drives job polarization. The right panel of column (3) shows the interaction effects of upper-tail log income inequality with a vector of industry dummies. These point estimates thus capture the idea that in countries with higher relative top-earnings, high-income workers could buy more market provided services using relatively cheap labor intensively. However, the last two numbers of Table 9 show that the point estimates for personal services and hotels and restaurants are not significant – although positive for both and relatively high for hotels and restaurants. In conclusion, Table 9 does not provide much evidence in support of the idea that income or income inequality is at the root of job polarization.

To examine this more formally, we first estimate equation (9) to obtain point estimates on the task measures, offshorability, the wage, and industry marginal costs. Rather than relying on country-industry-year dummies as in Table 7A, we now condition on industry output. The point estimate on output is 0.94, confirming the assumption of constant returns to scale. The point estimate on industry marginal costs, given by $1/(1-\eta)$, is 1.13. We then substitute the estimated equation (10) given in column (3) of Table 9 for $\log Y_{ict}$ in equation (9) and use predictions to calculate counterfactual employment changes by wage percentile.

In particular, Figure 3 plots three different counterfactual employment share changes grouping occupation-industry cells into 1994 UK wage percentiles by cumulatively "switching off" channels that according to our model affect relative employment growth. The dashed line labeled "income, TBTC, offshoring" is the first counterfactual and allows for all variation used in the previous analysis to predict employment changes. This line shows a reasonable fit to the actual employment changes, although it somewhat underpredicts the increase in low-paid jobs relative to middle-paid jobs and somewhat overpredicts the increase in high-paid jobs relative to middle-paid jobs.

When we ignore the channels associated with income[25], allowing only for the direct impact of task-biased technological change and offshoring and its indirect impact through changes in relative output prices, the fit given by the dotted line in Figure 3 improves, more accurately mirroring the relative increase in employment at both tails of the income distribution. While not reported in Figure 3, it can be shown that technological change and offshoring operate predominantly through their direct impacts on labor demand rather than indirectly through changes in relative output

[25] This is done by recalculating counterfactual employment while no longer allowing the coefficient on log income to vary by industry and setting the coefficients on industry dummies interacted with wage inequality equal to zero.

prices – when we switch off the impact of changes in relative output prices[26], we are able to predict only slightly less of the relative increase in low-paid jobs.

Lastly we also switch off the direct employment impact of offshoring[27], to give counterfactual employment changes exclusively associated with the effects of task-biased technological change, given by the dashed-dotted line in Figure 3. Although the fit that also allows for the direct effect of offshoring is slightly better, the difference is small, with task-biased technological change being able to predict most of the actual changes in jobs' employment shares.[28]

In sum, we therefore conclude that task-biased technological progress and, although to a much lesser degree, offshoring account for most employment polarization in Europe – changes in income or income inequality are less important. The pervasiveness of job polarization across our sample of 16 European countries due to task-biased technological progress sheds an important light on the working of our labor markets and calls for a better understanding of changes in relative employment

[26] Achieved by deducting $1/(1-\gamma)\log\Gamma_{ict}$ from the dotted line in Figure 3.

[27] By setting the coefficient on offshorability equal to zero. Note that this only eliminates the direct impact of offshoring- we cannot separate the indirect impact of offshoring on employment via relative prices out from the indirect impact of technological change.

[28] In this section, we have used all the variation in industry marginal costs to calculate counterfactual employment – however, this is not correct since only part of that variation is due to technological progress (and offshoring). To account for this, we first predict changes in industry marginal costs exclusively due to technological change as follows:

$$\Delta c_{ic} = -\sum_j \beta_{RTI*tt} * RTI * tt * s_{ijc}$$

where β_{RTI*tt} is the point estimate on a linear timetrend multiplied by the standardized routine task intensity index (defined as Routine/(Abstract+Service), with mean zero and unit standard deviation) from the conditional labor demand equation which also controls for offshoring; and s_{ijc} is the share of employment of occupation *j* in industry *i* in country *c* averaged across all years; the expression is multiplied by minus one to account for the fact that productivity has decreased and hence industry marginal costs have increased in routine intensive occupations. We then take these predicted changes in industry marginal costs and add them to the industry marginal costs in the initial year for each country to get an alternative time series for industry marginal costs that only takes cost changes caused by TBTC into account. We use the log of this series to calculate our TBTC-only counterfactuals. When calculating counterfactuals for both the TBTC and offshoring channels, we simply add the point estimate for offshoring to the calculation as follows:

$$\Delta c_{ic} = -\sum_j \left(\beta_{RTI*tt} * RTI + \beta_{OFF*tt} * OFF\right) * tt * s_{ijc}$$

It turns out that our simulated industry marginal costs very closely mimic actual industry marginal costs. It is not surprising, therefore, that when we use the simulated costs in calculating the counterfactuals, we find a picture that is virtually identical to the reported Figure 3. Also note that this alternative procedure has the added benefit of allowing us to separate out the indirect impact of technological change from the indirect impact of offshoring – again, however, this does not affect our results.

and wages due to changes in the demand for and supply of skills other than the level of education or income.

6. CONCLUSIONS

The recent changes in the European employment structure have been shown to be similar to those taking place in the US and the UK. In Western European countries, the employment shares of high-paid professionals and managers as well as low-paid personal services workers have increased at the expense of the employment shares of manufacturing and routine office workers. In other words, at least since the early nineties, there has been pervasive employment polarization in Western Europe too. We investigate to what extent these structural employment changes can be explained by the routinization hypothesis and offshoring.

We conclude that production technologies have become more intense in the use of non-routine tasks at the expense of routine tasks. In line with the routinization hypothesis, pervasive task-biased technological change has lead to an increase in the relative demand for and employment of non-routine workers in both low-paid and high-paid jobs in services. Without making any assumptions ex-ante about which occupations are more offshorable, our data also suggest that it is mainly manual jobs in manufacturing as well as office clerks that have been offshored. Since these jobs largely consist of doing routine tasks, offshoring could also explain part of the observed changes in occupational employment. We do find scope for the offshoring hypothesis, although the estimated impact is smaller and less pervasive relative to the impact of technological change. Finally, there is little support for the hypotheses that institutions or changes in income have had an important impact on employment structure.

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Figure 1. European-Wide Polarization, 1993-2006

Figure 2. Abstract, Routine, and Service task importances and offshorability for 21 occupations ordered by the 1993 mean European wage

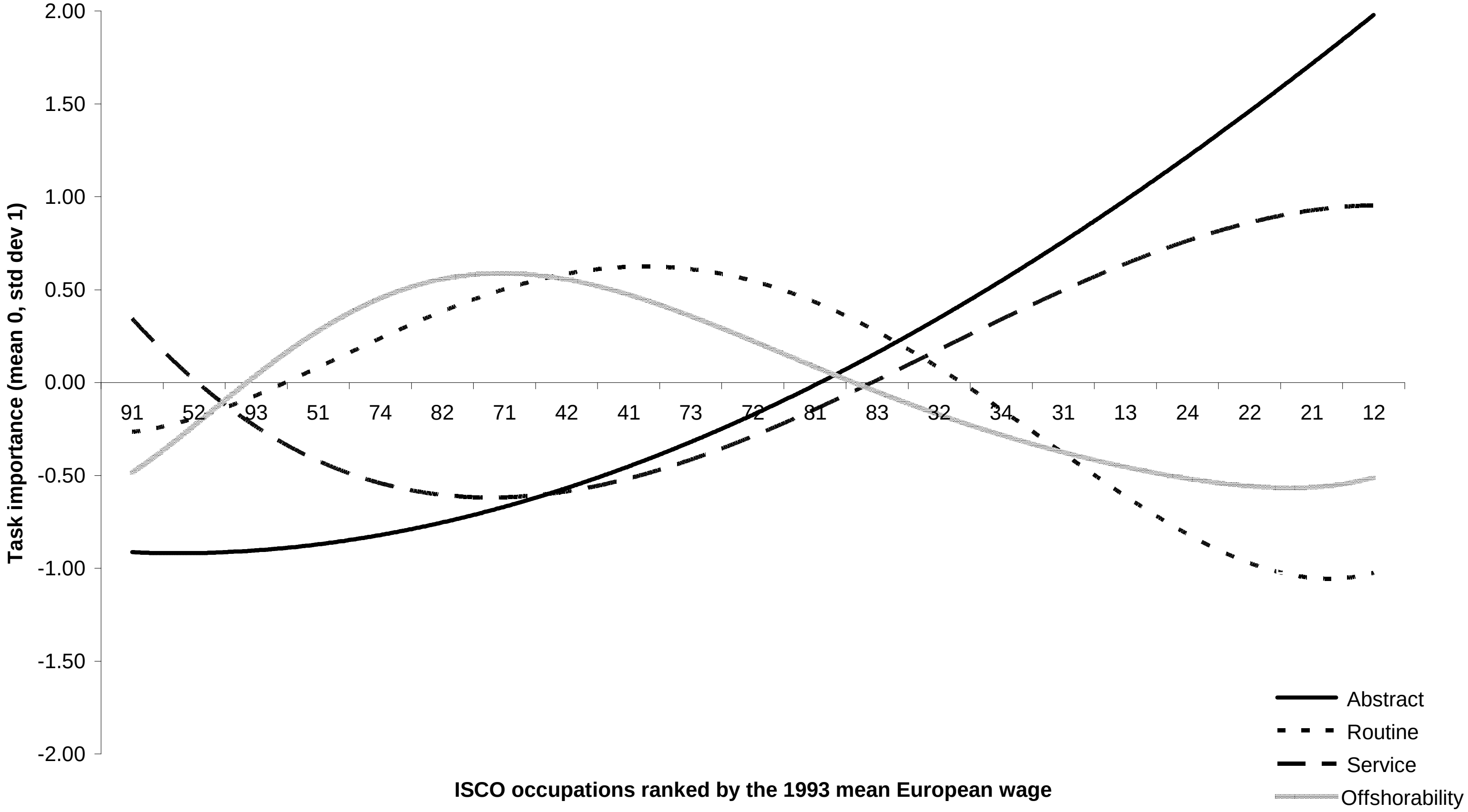

Figure 3. Actual and Counterfactual Smoothed Changes in Employment by Occupation-Industry, 1993-2006

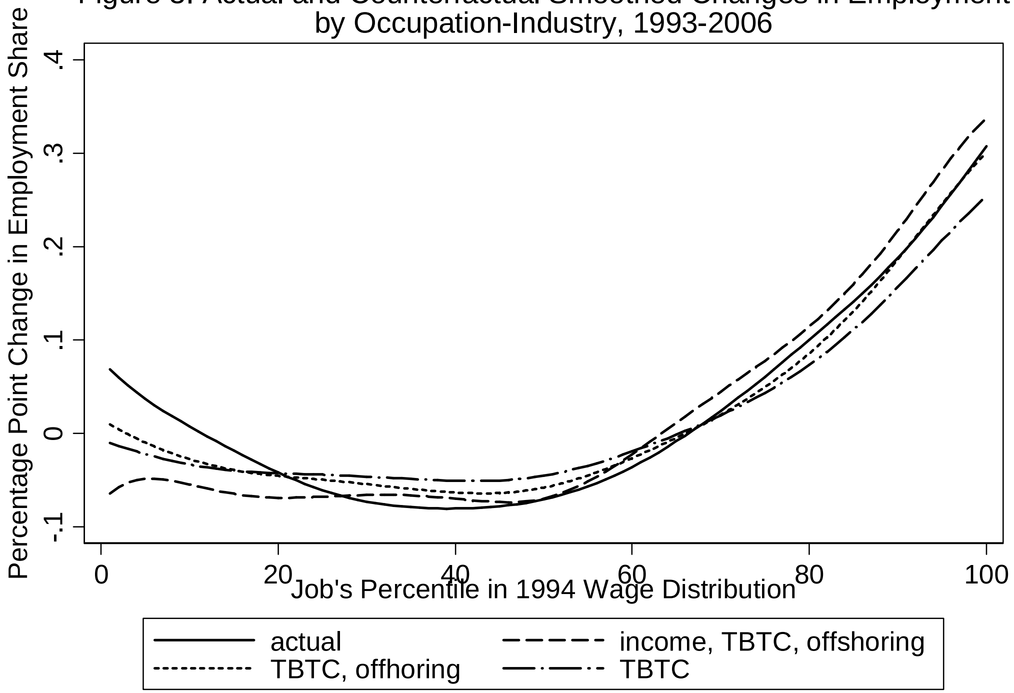

Table 1. Levels and changes in the shares of hours worked 1993- 2006 for occupations ranked by their mean 1993 European wage

Occupations ranked by 1993 mean European wage	ISCO code	Average employment share in 1993	Percentage point change over 1993-2006
Corporate managers	12	4.54%	1.25
Physical, mathematical and engineering professionals	21	2.92%	1.02
Life science and health professionals	22	1.86%	- 0.13
Other professionals	24	2.82%	0.70
Managers of small enterprises	13	3.60%	1.28
Physical, mathematical and engineering associate professionals	31	3.99%	0.91
Other associate professionals	34	6.77%	2.07
Life science and health associate professionals	32	2.28%	0.66
Drivers and mobile plant operators	83	5.48%	- 0.17
Stationary plant and related operators	81	1.75%	- 0.39
Metal, machinery and related trade work	72	8.33%	- 2.33
Precision, handicraft, craft printing and related trade workers	73	1.31%	- 0.40
Office clerks	41	12.04%	- 1.98
Customer service clerks	42	2.00%	0.19
Extraction and building trades workers	71	8.17%	- 0.52
Machine operators and assemblers	82	6.71%	- 2.01
Other craft and related trade workers	74	3.19%	- 1.37
Personal and protective service workers	51	6.94%	1.15
Laborers in mining, construction, manufacturing and transport	93	4.11%	0.48
Models, salespersons and demonstrators	52	6.73%	- 1.42
Sales and service elementary occupations	91	4.47%	1.02

Notes: Years 1993- 2006. All 16 countries, pooled. Employment shares in 1993 and/or 2006 imputed on the basis of average annual growth rates for countries in with shorter data spans. Occupations are ordered by their mean wage rank in 1993 across the 16 European countries, unweighted.

Table 2. Initial shares of hours worked and percentage changes over 1993- 2006 for high- , middling and low-paying occupations

	4 lowest paying occupations ^		9 middling occupations ^		8 highest paying occupations ^	
	Employment share in 1993	Percentage point change over 1993-2006	Employment share in 1993	Percentage point change over 1993-2006	Employment share in 1993	Percentage point change over 1993-2006
Austria	23%	- 0.59	53%	- 14.58	25%	15.17
Belgium	17%	1.48	49%	- 9.50	34%	8.03
Denmark	24%	- 0.96	40%	- 7.16	36%	8.13
Finland	18%	6.66	39%	- 6.54	43%	- 0.12
France	22%	- 0.74	48%	- 12.07	30%	12.81
Germany	22%	3.04	56%	- 8.72	22%	5.67
Greece	22%	1.75	48%	- 6.08	31%	4.34
Ireland	19%	6.19	46%	- 5.47	35%	- 0.72
Italy	27%	- 8.20	51%	- 9.08	22%	17.28
Luxembourg	22%	- 1.66	50%	- 8.45	28%	10.10
Netherlands	17%	2.27	38%	- 4.68	45%	2.41
Norway	23%	4.96	39%	- 6.52	38%	1.57
Portugal	26%	2.39	47%	- 1.13	27%	- 1.26
Spain	28%	0.96	49%	- 7.04	23%	6.07
Sweden	22%	1.91	42%	- 6.96	37%	5.04
UK	17%	5.77	44%	- 10.32	39%	4.55
EU average	22%	1.58	46%	- 7.77	32%	6.19

Notes: Years 1993- 2006. Occupational employment pooled within each country. ^ According to the mean 1993 European occupational wage rank.

Table 3. Real monthly wages of occupations across 16 European countries in 1993 and 2006, sorted by 1993 wage rank

Occupations ranked by the 1993 mean European wage	ISCO code	Real monthly wage in 2000 Euros 1993	2006	Standardized wage rank 1993	2006
Corporate managers	12	3,472	3,724	1.70	1.60
Physical, mathematical and engineering professionals	21	3,038	3,170	1.43	1.47
Life science and health professionals	22	2,720	3,164	1.22	1.39
Other professionals	24	2,712	2,910	1.17	1.26
Managers of small enterprises	13	2,653	2,685	1.15	0.93
Physical, mathematical and engineering associate professionals	31	2,150	2,324	0.74	0.80
Other associate professionals	34	2,115	2,227	0.74	0.69
Life science and health associate professionals	32	1,915	2,018	0.39	0.28
Drivers and mobile plant operators	83	1,789	1,916	0.05	-0.04
Stationary plant and related operators	81	1,793	1,954	0.01	-0.03
Metal, machinery and related trade work	72	1,748	1,927	- 0.01	0.02
Precision, handicraft, craft printing and related trade workers	73	1,733	1,968	- 0.09	-0.02
Office clerks	41	1,679	1,865	- 0.36	-0.15
Customer service clerks	42	1,613	1,732	- 0.50	-0.50
Extraction and building trades workers	71	1,624	1,750	- 0.58	-0.61
Machine operators and assemblers	82	1,565	1,728	- 0.73	-0.61
Other craft and related trade workers	74	1,504	1,598	- 0.89	-0.99
Personal and protective service workers	51	1,424	1,538	- 1.13	-1.05
Laborers in mining, construction, manufacturing and transport	93	1,402	1,518	- 1.22	-1.22
Models, salespersons and demonstrators	52	1,237	1,344	- 1.43	-1.50
Sales and service elementary occupations	91	1,112	1,242	- 1.68	-1.70

Notes: Mean occupational wages weighted by weekly hours worked in each country in 1993 and 2006 calculated on the basis of ECHP, EU-SILC and OECD wage data: unweighted average across countries. Average unweighted wage rank across countries. Rank rescaled to mean zero and unit standard deviation. The correlation between the two wage ranks is 0.994.

Table 4. Abstract, Routine, and Service task importances, offshorability, and mean education levels for occupations ordered by their mean 1993 European wage

Occupations ranked by 1993 mean European wage	ISCO code	Abstract task importance^ (1)	Routine task importance^ (2)	Service task importance^ (3)	Offshora-bility^^ (4)	Mean education level^^^ (5)
Corporate managers	12	1.80	-1.18	1.15	-0.59	2.05
Physical, mathematical and engineering professionals	21	1.50	-0.86	-0.35	-0.37	2.83
Life science and health professionals	22	1.47	-0.16	1.73	-0.64	2.92
Other professionals	24	1.29	-1.63	1.14	-0.51	2.69
Managers of small enterprises	13	1.80	-1.18	1.15	-0.59	2.05
Physical, mathematical and engineering associate professionals	31	0.89	0.20	-0.44	-0.27	2.22
Other associate professionals	34	0.75	-1.37	0.93	-0.12	2.14
Life science and health associate professionals	32	0.36	0.21	0.86	-0.64	2.40
Drivers and mobile plant operators	83	-0.59	1.33	0.01	-0.63	1.46
Stationary plant and related operators	81	-0.49	1.33	-1.21	1.63	1.56
Metal, machinery and related trade work	72	0.43	1.16	-0.29	0.29	1.68
Precision, handicraft, craft printing and related trade workers	73	-1.30	0.81	-1.79	-0.62	1.69
Office clerks	41	-0.42	-1.29	0.04	1.21	1.91
Customer service clerks	42	-0.36	-0.82	0.74	-0.27	1.89
Extraction and building trades workers	71	-0.23	0.98	-0.64	-0.59	1.55
Machine operators and assemblers	82	-0.46	1.31	-1.33	3.18	1.48
Other craft and related trade workers	74	-1.36	0.67	-1.30	-0.27	1.57
Personal and protective service workers	51	-0.37	-0.16	0.82	-0.64	1.67
Laborers in mining, construction, manufacturing and transport	93	-1.00	0.52	-0.53	0.87	1.41
Models, salespersons and demonstrators	52	-0.53	-0.94	1.00	-0.64	1.66
Sales and service elementary occupations	91	-1.38	-0.11	-0.55	-0.37	1.40

Notes: Occupations ordered by their mean wage rank (wages weighted by hours worked) in 1993 across the 16 European countries, countries unweighted. ^ Source: ONET. Rescaled to mean 0 and standard deviation 1, a higher value means a task is more important. Values for ISCO 12 and 13 are identical because ONET SOC codes do not allow distinction between these two ISCO occupations. ^^ Source: European Restructuring Monitor. Rescaled to mean 0 and standard deviation 1, a higher value means more offshorable. Values for ISCO 12 and 13 have been made the same by taking the mean weighted by hours worked. ^^^ Source: ELFS. Weighted by hours worked. 1=up to and including lower secondary education, 2=upper secondary and post-secondary (non-tertiary) education, 3=tertiary or post-graduate education. Unweighted mean across all countries, for the first year in which education data was available (usually 1999). Values for ISCO 12 and 13 have been made the same by taking the mean weighted by hours worked.

Table 5. Shiftshare analysis of changes in share of hours worked between and within industries for occupations ranked by the mean 1993 European wage

Occupations ranked by 1993 mean European wage	ISCO code	Total change in occupational employment share	Change in employment share within industries	Change in employment share between industries
Corporate managers	12	1.23	1.26	- 0.02
Physical, mathematical and engineering professionals	21	1.02	0.71	0.31
Life science and health professionals	22	- 0.12	- 0.41	0.29
Other professionals	24	0.65	0.03	0.62
Managers of small enterprises	13	1.25	1.20	0.06
Physical, mathematical and engineering associate professionals	31	0.87	0.81	0.06
Other associate professionals	34	2.15	1.37	0.79
Life science and health associate professionals	32	0.69	0.22	0.47
Drivers and mobile plant operators	83	- 0.18	0.09	- 0.27
Stationary plant and related operators	81	- 0.38	- 0.02	- 0.36
Metal, machinery and related trade work	72	- 2.29	- 1.12	- 1.17
Precision, handicraft, craft printing and related trade workers	73	- 0.39	- 0.18	- 0.22
Office clerks	41	- 1.93	- 2.26	0.33
Customer service clerks	42	0.18	0.11	0.07
Extraction and building trades workers	71	- 0.50	- 0.21	- 0.29
Machine operators and assemblers	82	- 1.96	- 0.69	- 1.27
Other craft and related trade workers	74	- 1.35	- 0.75	- 0.59
Personal and protective service workers	51	1.06	- 0.08	1.14
Laborers in mining, construction, manufacturing and transport	93	0.46	0.80	- 0.35
Models, salespersons and demonstrators	52	- 1.38	- 0.93	- 0.45
Sales and service elementary occupations	91	0.90	0.05	0.85

Notes: Years 1993- 2006. All 16 countries, pooled. Between and within effects may not exactly add up to the total change due to rounding errors. All numbers are percentage points.

Table 6. Analysis of variance for employment
Dependent variable: log(hours worked/1000)

	(1)	(2)	(3)
F- statistics for interactions:			
Country* Year	398.00 (0.000)	378.86 (0.000)	40.42 (0.000)
Industry*Country* Year	3.12 (0.000)	2.86 (0.000)	3.66 (0.000)
Industry*Occupation	439.23 (0.000)	415.71 (0.000)	546.96 (0.000)
Occupation*Year	2.77 (0.000)	2.59 (0.000)	2.27 (0.000)
Industry*Occupation*Year	-	0.66 (1.000)	0.81 (1.000)
Occupation*Country*Year	-	-	0.89 (1.000)
F- statistic (model)	101.89 (0.000)	50.31 (0.000)	40.78 (0.000)
R^2	0.887	0.893	0.928

Notes: Years 1993- 2006; all countries; 36,366 observations for each ANOVA. F-statistics reported, corresponding p- values in brackets. Specifications in columns (1) and (2) control for occupation, and the specification in column (3) controls for occupation*country.

Table 7A. Conditional effect of task importance and offshorability on employment
Dependent variable: log(hours worked/1000)

Linear time- trend interacted with:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ABSTRACT task importance	1.71*	-	-	-	1.57*	-	-	1.11*	1.12*
	(0.14)				(0.14)			(0.17)	(0.17)
ROUTINE task importance	-	- 1.57*	-	-	-	- 1.40*	-	- 0.74*	- 0.75*
		(0.13)				(0.13)		(0.17)	(0.17)
SERVICE task importance	-	-	1.58*	-	-	-	1.45*	0.44*	0.26
			(0.15)				(0.16)	(0.21)	(0.22)
Offshorability	-	-	-	- 0.97*	- 0.59*	- 0.56*	- 0.30	-	- 0.36*
				(0.15)	(0.15)	(0.15)	(0.16)		(0.16)
Log wage	- 0.49*	- 0.47*	- 0.48*	- 0.50*	- 0.48*	- 0.47*	- 0.48*	- 0.47*	- 0.47*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
R^2	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89

Notes: Years 1993- 2006; all countries; 34,816 observations for each regression. Each regression includes dummies for occupation- industry cells and for industry- country- year cells. Task importances and offshorability have been rescaled to mean 0 and standard deviation 1. All point estimates and standard errors, except for those on the log wage, have been multiplied by 100. Standard errors clustered by country- industry- occupation. *Significant at the 5% level or better.

Table 7B. Conditional effect of task importance, education and offshorability on employment
Dependent variable: log(hours worked/1000)

Linear time- trend interacted with:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ABSTRACT task importance	-	1.03*	-	-	-	1.06*	-	-	0.82*	0.92*
		(0.25)				(0.25)			(0.27)	(0.27)
ROUTINE task importance	-	-	- 0.90*	-	-	-	- 0.83*	-	- 0.63*	- 0.67*
			(0.17)				(0.16)		(0.20)	(0.21)
SERVICE task importance	-	-	-	0.96*	-	-	-	0.88*	0.48*	0.30
				(0.17)				(0.18)	(0.22)	(0.23)
Education level	1.68*	0.83*	1.17*	1.17*	1.53*	0.64*	1.09*	1.15*	0.39	0.28
	(0.15)	(0.26)	(0.14)	(0.16)	(0.15)	(0.26)	(0.18)	(0.17)	(0.29)	(0.29)
Offshorability	-	-	-	-	- 0.49*	- 0.52*	- 0.39*	- 0.20	-	- 0.33*
					(0.15)	(0.15)	(0.15)	(0.16)		(0.16)
Log wage	- 0.48*	- 0.48*	- 0.47*	- 0.48*	- 0.48*	- 0.48*	- 0.47*	- 0.48*	- 0.47*	- 0.47*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
R^2	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89

Notes: Years 1993- 2006; all countries; 34,816 observations for each regression. Each regression includes dummies for occupation-industry cells and for industry- country- year cells. Task importances, the education level and offshorability have been rescaled to mean 0 and standard deviation 1. All point estimates and standard errors, except for those on the log wage, have been multiplied by 100. Standard errors clustered by occupation- country- industry. *Significant at the 5% level or better.

Table 7C. Conditional effect of task importance, education and offshorability on the 13 lowest- paying occupations
Dependent variable: log(hours worked/1000)

Linear time- trend interacted with:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ROUTINE task importance	-	- 0.78* (0.16)	- 0.94* (0.21)	-	-	-	- 0.84* (0.21)	-	- 0.29 (0.22)	- 0.29 (0.22)
SERVICE task importance	-	-	-	1.10* (0.19)	1.18* (0.20)	-	-	1.15* (0.22)	1.04* (0.22)	1.01* (0.24)
Education level	0.34* (0.16)	-	- 0.25 (0.21)	-	- 0.18 (0.17)	0.31 (0.16)	- 0.21 (0.22)	- 0.17 (0.18)	- 0.30 (0.21)	- 0.29 (0.22)
Offshorability	-	-	-	-	-	- 0.49* (0.17)	- 0.36* (0.17)	- 0.06 (0.19)	-	- 0.06 (0.19)
Log wage	- 0.23 (0.14)	- 0.21 (0.14)	- 0.21 (0.14)	- 0.20 (0.14)	- 0.20 (0.14)	- 0.23 (0.14)	- 0.21 (0.14)	- 0.20 (0.14)	- 0.20 (0.14)	- 0.20 (0.14)
R^2	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90

Notes: Years 1993- 2006; all countries; 22,491 observations for each regression. Each regression includes dummies for occupation- industry cells and for industry- country- year cells. Task importances, the education level and offshorability have been rescaled to mean 0 and standard deviation 1. All point estimates and standard errors, except for those on the log wage, have been multiplied by 100. Standard errors clustered by occupation- country- industry. *Significant at the 5% level or better.

Table 8: Institutions as an explanation for country-heterogeneity in the employment impact of technological change
Dependent variable: log(hours worked/1000)

	ABSTRACT			***ROUTINE***			***SERVICE***		
Linear time-trend interacted with:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
task importance	1.72*	1.72*	1.69*	-1.32*	-1.33*	-1.32*	1.35*	1.39*	1.36*
	(0.17)	(0.17)	(0.17)	(0.15)	(0.15)	(0.15)	(0.18)	(0.18)	(0.18)
task importance* log(p90/p10)	-0.17	-	-	0.17	-	-	-0.29	-	-
	(0.16)			(0.15)			(0.17)		
task importance* log(p90/p50)	-	-0.24	-	-	0.19	-	-	-0.33	-
		(0.15)			(0.15)			(0.17)	
task importance* log(p50/p10)	-	-	-0.23	-	-	0.08	-	-	-0.11
			(0.17)			(0.16)			(0.17)
offshorability	-0.53*	-0.53*	-0.53*	-0.54*	-0.53*	-0.54*	-0.28	-0.27	-0.28
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.18)	(0.18)	(0.18)
Log wage	-0.43*	-0.33*	-0.50*	-0.52*	-0.55*	-0.48*	-0.57*	-0.61*	-0.50*
	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
R^2	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89

Notes: Years 1993-2006, all countries except Austria, Greece, Luxembourg and Norway; 26,259 observations for each regression. All regressions contain dummies for occupation-industry cells and for industry-country-year cells. Task importances, offshorability and institutions have been rescaled to mean 0 and standard deviation 1. All point estimates and standard errors, except for the log wage, have been multiplied by 100. Standard errors clustered by country-industry-occupation. *Significant at the 5% level or better.

Table 9. Product demand
Dependent variable: Log(industry output)

	(1)	(2)	(3)	
Log industry marginal costs	- 0.66*	- 0.88*	- 0.89*	
	(0.31)	(0.32)	(0.33)	
Log income/capita	0.92*	-	-	-
	(0.10)			
Log population	1.00*	0.99*	0.99*	
	(0.02)	(0.02)	(0.02)	
		Measure	Measure	
			(a)	(b)
		Log income /capita	Log income /capita	Log income inequality
Measure interacted with manufacturing	-	1.00*	0.73*	- 0.06
		(0.18)	(0.18)	(0.04)
Deviation from interaction with manufacturing:				
Electricity, gas and water supply	-	- 0.21	0.12	0.07
		(0.29)	(0.33)	(0.07)
Financial intermediation	-	0.20	0.74*	0.12*
		(0.28)	(0.30)	(0.06)
Real estate, renting and business activity	-	0.65*	1.36*	0.16*
		(0.26)	(0.40)	(0.08)
Transport, storage and communication	-	0.31	0.32	0.00
		(0.21)	(0.24)	(0.06)
Construction	-	- 0.66*	- 0.26	0.09
		(0.22)	(0.24)	(0.06)
Wholesale and retail	-	- 0.05	0.40	0.10
		(0.31)	(0.28)	(0.06)
Health and social work	-	0.43	0.30	- 0.03
		(0.28)	(0.42)	(0.10)
Other community, social and personal service activities	-	- 0.22	0.04	0.06
		(0.30)	(0.25)	(0.08)
Hotels and restaurants	-	- 1.52*	- 0.65	0.20
		(0.35)	(0.49)	(0.11)
Observations	1,820	1,260	1,260	
R^2	0.96	0.98	0.98	

Notes: Years 1993- 2006; all countries, except Ireland, Sweden and the UK in first column; and Austria, Greece, Ireland, Luxembourg, Norway, Sweden and the UK in the second and third columns; industry "Private household with employed persons" included in "Other community, social.." for France, Portugal, and Spain. Each regression includes dummies for industry cells. Industries ranked by their mean gross real hourly UK wage in 1994; the rank of manufacturing is 6. Log income inequality is log(p90/p50) averaged over 1990- 1994 and rescaled to mean 0 and standard deviation 1. Standard errors clustered by country- industry. *Significant at the 5% level or better.